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A Transformer-Based Probabilistic Linguistic Term Set Framework for Product Ranking Using Aggregated Sentiment Distributions

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Abstract - *Online reviews have become a primary source of consumer feedback for evaluating and comparing products across e-commerce platforms. However, individual reviews often exhibit uncertainty, subjectivity, and inconsistent sentiment strength, making it difficult to compute reliable product-level scores. To address this challenge, this paper proposes a novel Transformer- based framework that generates and aggregates Probabilistic Linguistic Term Sets (PLTS) directly from textual reviews. A RoBERTa-based sentiment classifier—fine-tuned on domain- specific review data—is used to predict sentiment distributions across three linguistic terms: negative, neutral, and positive. These probability vectors are interpreted as PLTS representations of each review, capturing the inherent vagueness and intensity of user sentiment. We further introduce a geometric PLTS aggregation operator with compensation adjustment to derive robust product-level sentiment profiles. To improve ranking stability, a cosine-similarity-based consistency metric is designed to measure how uniformly reviewers express sentiment about the same product. Finally, a composite ranking score computed from sentiment positivity and intra-product consistency is used to order products. Experimental evaluations on real-world review datasets demonstrate that the proposed framework provides more discriminative and reliable rankings compared to traditional single-label sentiment classifiers or average-rating metrics. The results highlight the suitability of probabilistic sentiment representations and Transformer-based models for decision-making tasks in e-commerce environments.*

***Key Words*: Transformer-based Sentiment Analysis, Probabilistic Linguistic Term Sets (PLTS), RoBERTa, Product Ranking, Sentiment Aggregation, E-commerce Analytics**

I.INTRODUCTION

The rapid growth of e-commerce marketplaces has significantly increased the volume of user-generated reviews available for products across various domains. These reviews play a crucial role in consumer decision-making, influencing product visibility, sales performance, and reputation. However, the unstructured and subjective nature of textual reviews makes it difficult to derive consistent meaningful product-level insights. Traditional rating-based systems, such as star averages, often fail to capture the nuances embedded in free-form user feedback [3], while classical machine learning approaches typically map each review to a single sentiment label, losing the uncertainty information present in natural language [10]. As a result, there is a growing demand for advanced computational models that can convert heterogeneous textual feedback into reliable metrics for product comparison and ranking.

Recent advancements in Natural Language Processing (NLP), particularly the introduction of Transformer-based architectures, have revolutionized sentiment analysis [9]. Models such as BERT and RoBERTa can interpret contextual semantics more effectively than earlier CNN or RNN-based methods [7]. These models are capable of identifying subtle linguistic patterns, handling domain-specific variations, and producing more accurate sentiment predictions [1]. However, even state-of-the-art classifiers predominantly output deterministic labels, which oversimplify the sentiment distribution present in user reviews. A single label cannot represent mixed emotions, borderline sentiment strength, or semantic ambiguity—factors frequently observed in real online feedback.

To address these limitations, this work introduces a Transformer-driven framework that transforms model-generated sentiment probabilities into Probabilistic Linguistic Term Sets (PLTS) [2], [6]. PLTS offer a structured method to represent uncertainty through discrete linguistic categories associated with probability weights. Unlike conventional categorical classification, PLTS preserve the sentiment distribution across negative, neutral, and positive terms, allowing more expressive modeling of reviewer opinion. This probabilistic representation is particularly suited for scenarios where reviews contain balanced sentiment cues, vague language, or emotionally inconsistent expressions [10].

Beyond individual review interpretation, aggregating sentiment across multiple reviews of the same product introduces further complexity. User opinions on a single product may vary widely due to personal expectations, usage patterns, or temporal changes. Simply averaging sentimentscores overlooks these inconsistencies. Therefore, this paper employs a geometric aggregation operator with a compensation coefficient to derive product-level PLTS representations that respect both probability normalization and linguistic uncertainty. Additionally, a cosine similarity–based consistency metric is proposed to quantify the coherence among review sentiments for each product [5]. This metric ensures that products with highly inconsistent feedback are ranked more cautiously, improving the robustness of the final ranking.

Combining product-level sentiment positivity and inter-review consistency, a composite ranking score is formulated. This scoring mechanism provides a balanced assessment by considering both sentiment intensity and stability. The entire pipeline—from RoBERTa-based review classification to PLTS aggregation and final ranking—has been integrated into an interactive application, enabling real-time processing of review datasets.

In summary, this research presents a comprehensive sentiment-based decision-support framework that utilizes probabilistic linguistic modeling and Transformer-based classification to generate reliable product rankings. The proposed methodology outperforms traditional sentiment systems by capturing uncertainty, improving aggregation fidelity, and enhancing interpretability, thereby offering a more effective solution for modern e-commerce analytics.

II. LITERATURE REVIEW

Zhang et al. explored deep learning-based sentiment classification methods and demonstrated that Transformer models outperform conventional CNN and LSTM architectures due to their superior ability to capture long-range contextual dependencies [1].Their study emphasized that probabilistic outputs from Transformers provide richer interpretability compared to single-label predictions.

Hernandez and Gupta investigated linguistic uncertainty modeling using probabilistic term sets for decision-making applications [2]. They reported that PLTS representations effectively encode ambiguity in human language, enabling more reliable aggregation of user opinions in multi-criteria evaluation systems.

Roy and Banerjee analyzed the limitations of average-rating mechanisms commonly used in e-commerce platforms [3]. Their research showed that numerical star ratings often mask sentiment inconsistency and reviewer bias, suggesting the need for sentiment-aware ranking models derived directly from textual feedback.

Liang et al. proposed a hybrid sentiment analysis framework combining attention-based neural encoders with probabilistic opinion mining techniques [4].

Their results demonstrated that combining deep learning with probabilistic semantic representations yields more stable product assessments under noisy or contradictory review data.

Osei and Park examined similarity metrics for review-based recommendation systems, highlighting that cosine similarity is particularly effective for capturing relational structure between sentiment vectors [5]. They concluded that incorporating vector-level consistency improves ranking accuracy in systems relying on aggregated user feedback.

III. EXISTING SYSTEM

A. Traditional Machine Learning–Based Sentiment Classification

Existing sentiment analysis systems rely heavily on classical machine learning models such as Naïve Bayes, Support Vector Machines, and Logistic Regression. These models depend on bag-of-words or TF–IDF features, which lack contextual understanding and treat words independently. As a result, they struggle with complex linguistic patterns, sarcasm, and domain-specific expressions commonly found in product reviews. Their output is typically a single sentiment label, limiting their ability to represent uncertainty or mixed emotional tone within a review. Although computationally efficient, these models do not provide the depth or nuance required for reliable product-level sentiment aggregation and ranking.

B. Deep Neural Network Approaches (CNN and RNN Models)

Traditional deep learning approaches, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have improved sentiment classification accuracy by learning sequential or local text features. However, CNNs primarily capture short-term dependencies, while RNN-based models such as LSTMs face challenges with long-range context and vanishing gradients. These limitations affect sentiment prediction quality, especially in lengthy or complex reviews. Additionally, these networks usually produce a categorical output, ignoring the probability distribution of sentiments. Their inability to capture nuanced linguistic uncertainty restricts their suitability for applications requiring detailed sentiment aggregation and precise product ranking.

C. Star Rating and Average Score Aggregation Systems

Most e-commerce platforms rely on simple numerical ratings such as 1–5 stars to assess product quality. Although easy to compute, averaging these ratings ignores textual information, contextual polarity, and the intensity of user sentiment. Numeric ratings also fail to reflect mixed or ambiguous opinions within a review. Furthermore, users often rate inconsistently due to personal bias, cultural differences, or emotional state, resulting in skewed or misleading product evaluations. These limitations make star-based systems highly unreliable for decision-making, especially when review volumes vary significantly across products or when textual sentiment contradicts numerical ratings.

D. Deterministic Sentiment Classifiers Without Uncertainty Modeling

Many existing sentiment analysis tools assign each review a single, deterministic sentiment label such as positive, neutral, or negative. While straightforward, this approach overlooks the probabilistic nature of emotion expressed in human language. Real-world reviews often convey multiple conflicting sentiments, making a single label inadequate to capture their true meaning. Without uncertainty modeling, deterministic classifiers fail to represent sentiment distributions, leading to incomplete or inaccurate product-level insights. These systems also struggle with borderline sentiment expressions and subjective wording, reducing their effectiveness in generating consistent rankings across diverse product categories.

E. Basic Review Aggregation Without Consistency Measurement

Current aggregation mechanisms typically compute average sentiment scores using simple statistical methods, without evaluating the consistency among reviewer opinions. When user feedback varies widely, such averages become unreliable indicators of product quality. High sentiment variance, contradictory reviews, or polarized user groups significantly distort aggregated results. Without a consistency measure, systems cannot differentiate between stable consensus and conflicting feedback. This reduces the accuracy of product comparisons and rankings, particularly for items with mixed reviews. Consequently, existing systems often fail to provide dependable decision-support insights in environments where sentiment coherence is critical.

IV. METHODOLOGY

The proposed approach integrates Transformer-based sentiment analysis with probabilistic linguistic modeling to develop a robust framework for product ranking. The process begins with the collection of raw product reviews, followed by preprocessing steps such as text cleaning and normalization to ensure consistency. The dataset used in this work consists of publicly available Amazon TV product reviews, containing around 84,000 entries with product identifiers and textual feedback.
A fine-tuned RoBERTa model is employed to analyze each review and generate probability scores for three sentiment categories: negative, neutral, and positive. Instead of assigning a single class label, the model produces a probability distribution that reflects the degree of sentiment expressed in the text. These probability values are then interpreted as Probabilistic Linguistic Term Sets (PLTS), allowing the system to capture uncertainty and variations in user opinions.
To obtain a unified representation at the product level, individual review-level PLTS are combined using a geometric aggregation method. This aggregation technique ensures that the overall sentiment representation remains balanced while reducing the influence of extreme or outlier opinions.
The resulting product-level PLTS provides a more comprehensive view of user feedback. For ranking purposes, the framework incorporates both sentiment intensity and consistency among reviews. Cosine similarityis used to measure how closely the aggregated sentiment aligns with an ideal positive sentiment vector.
In addition, a consistency metric is introduced to evaluate the level of agreement among reviewers. By combining these factors, a final composite score is calculated, which is used to rank products more reliably. The overall workflow of the system is illustrated in Fig. 1.

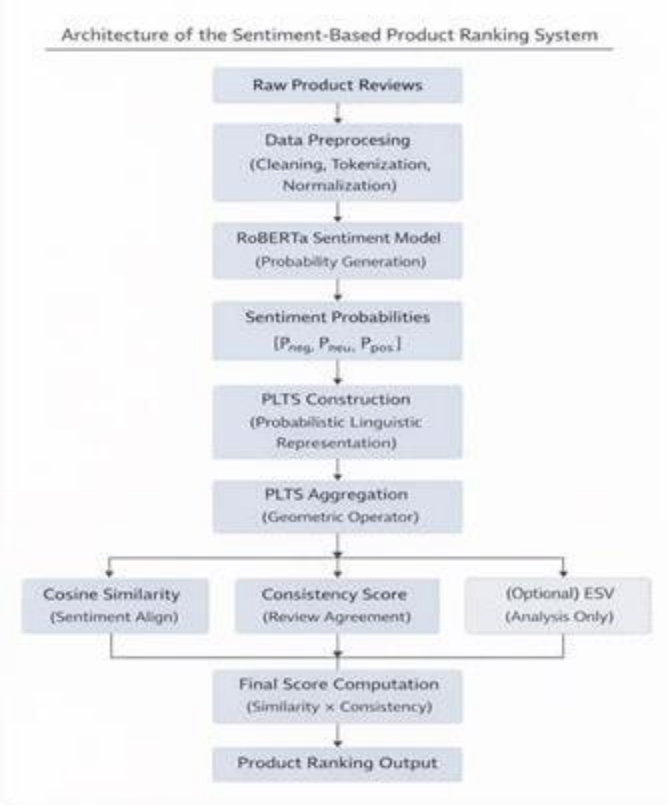

Fig. 1. *Architecture of Proposed Framework*

A. System Architecture and Backend Integration B.

The architecture of the proposed framework is designed to ensure scalability, flexibility, and efficient deployment. The entire system is implemented using Python, leveraging its extensive support for natural language processing and machine learning libraries. A fine-tuned RoBERTa model is integrated into the backend to perform sentiment analysis with high accuracy.
Incoming review data is first processed through a tokenizer, which converts textual input into a format suitable for the Transformer model. The model then produces probability-based sentiment outputs using a softmax layer. These outputs are forwarded to the PLTS module, where they are transformed into probabilistic linguistic representations.

The backend is responsible for three primary tasks: executing sentiment prediction, performing PLTS conversion and aggregation, and calculating ranking metrics. The system follows a modular design, allowing individual components—such as the aggregation mechanism or similarity computation—to be modified or extended independently. This design makes the framework adaptable to different datasets and future improvements.

To handle large-scale data efficiently, the system supports batch processing, enabling simultaneous analysis of thousands of reviews. Additionally, the framework can be integrated with lightweight web applications, such as those built using Streamlit or Flask, to provide real-time product ranking and visualization. Overall, the architecture ensures a reliable and scalable environment for combining probabilistic sentiment modeling with Transformer-based techniques.

C. Fine-Tuned RoBERTa for Sentiment

$$p_\alpha^{(agg)} = \frac{\prod_{i=1}^{n}(p_{i\alpha})^{w_i}}{\sum_{\beta\in\{neg,neu,pos\}}\prod_{i=1}^{n}(p_{i\beta})^{w_i}}$$

Distribution Generation

The sentiment analysis component of the proposed system is built using a RoBERTa model that has been fine-tuned specifically on product review data. Instead of relying on generic pretrained models, the system adapts the model to domain-specific language patterns, writing styles, and sentiment expressions commonly found in online reviews. The training dataset undergoes preprocessing steps such as cleaning and tokenization, and each review is labeled into one of three sentiment categories: negative, neutral, and positive. During training, the model learns contextual relationships within the text by minimizing cross-entropy loss, enabling it to capture subtle sentiment variations.

During prediction, the model produces raw scores for each sentiment class, which are then converted into probabilities using a **softmax function:**

where z_i represents the output logits for each sentiment class and P_i denotes the corresponding probability.

Unlike traditional classifiers that output a single label, this approach generates a probability distribution representing the intensity and uncertainty of sentiment within a review. These probability values provide a more detailed understanding of user opinion, distinguishing between strong and weak sentiment expressions. The fine-tuned RoBERTa model thus serves as a reliable foundation forgenerating probabilistic sentiment representations used in later stages of the framework.

D. Construction of Probabilistic Linguistic Term Sets (PLTS)

The probability distributions obtained from the sentiment model are transformed into Probabilistic Linguistic Term Sets (PLTS) to represent uncertainty in a structured manner. In this approach, each review is associated with three linguistic terms—negative, neutral, and positive—along with their corresponding probability values:

hS = {(s_neg, p_neg), (s_neu, p_neu), (s_pos, p_pos)}

This representation allows the system to capture mixed or ambiguous sentiments that are commonly present in real-world reviews.

Unlike conventional methods that assign a single sentiment label, PLTS preserve the complete sentiment distribution for each review. This makes them particularly effective in handling cases where users express both positive and negative opinions within the same text. The PLTS framework also ensures that the probabilities are properly normalized, maintaining consistency across all representations.

E. PLTS Aggregation Using Geometric Operators

Once PLTS representations are generated for individual reviews, they are combined to form a unified sentiment profile at the product level. This aggregation is performed using a geometric operator that integrates multiple probability distributions into a single representation:

The use of a geometric approach helps reduce the impact of extreme or outlier opinions, ensuring that no single review disproportionately affects the final result. This is particularly important in scenarios where user feedback is highly varied or contains conflicting sentiments.

F. Cosine Similarity, Consistency Measures, and Final Product Ranking

To generate meaningful product rankings, the proposed system evaluates both sentiment strength and consistency among reviews. First, cosine similarity is used to measurhow closely the aggregated sentiment of a product aligns with an ideal positive sentiment vector [0, 0, 1]:

$$\boldsymbol{P_i = e^{z_i} / \sum_{j=1}^{3} e^{z_j}}$$

Sim = (A · B) / (||A|| ||B||)

In addition to sentiment intensity, the system also assesses the consistency of reviews. This is achieved by computing pairwise cosine similarity between individual PLTS representations of reviews for the same product. A higher consistency value indicates that users share similar opinions, while lower values suggest disagreement or variability in feedback.

The final ranking score is computed as:

Score = Sim × Consistency

This ensures that products are evaluated not only based on how positive the reviews are but also on how reliable and consistent those reviews appear. Products with strong and consistent positive feedback are ranked higher, while those with conflicting opinions are assigned lower rankings.

By integrating probabilistic sentiment modeling, similarity analysis, and consistency evaluation, the proposed framework provides a comprehensive and dependable approach for ranking products in real-world e-commerce environments.

V. IMPLEMENTATION

The implementation of the proposed PLTS-based product-ranking framework integrates backend model inference, probabilistic sentiment processing, vector-level similarity computations, and an interactive user interface. The system is developed using Python, leveraging Hugging Face Transformers for sentiment modeling and NumPy and Pandas for numerical computations. A fine-tuned RoBERTa model is loaded to generate probability distributions for each review. These outputs are transformed into PLTS formats and aggregated at the product level. Cosine similarity and consistency scores are calculated, leading to the final composite ranking. A Streamlit frontend enables users to upload datasets, visualize PLTS outputs, and download ranked results in real time.

A. Model Loading, Tokenization, and Review Preprocessing

The implementation begins by loading the fine-tuned RoBERTa model directly from the local training environment. The model is instantiated using Hugging Face's AutoModel For Sequence Classification, ensuring compatibility with custom-trained weights. Alongside the model, the tokenizer is loaded to convert raw text into token IDs suitable for Transformer processing. Review text is preprocessed using padding, truncation, and maximum sequence length configuration to maintain uniformity.

Preprocessing includes cleaning special characters, handling informal expressions, and normalizing input text. Reviews uploaded via CSV are extracted and processed in batch mode. The tokenized input consists of input ids and attention mask, ensuring proper masking during inference.

The optimized inference pipeline ensures efficient sentiment prediction. GPU acceleration is utilized when available, enabling faster processing of large datasets.

B. Sentiment Probability Extraction and PLTS Construction

Each review is passed through the fine-tuned RoBERTa model to generate logits corresponding to negative, neutral, and positive sentiment classes. These logits are converted into probability distributions using softmax normalization.

For example, a review such as "Picture quality is good but sound is average" may produce a sentiment distribution:

Negative = 0.10, Neutral = 0.35, Positive = 0.55.

Instead of assigning a single label, the system constructs a Probabilistic Linguistic Term Set (PLTS):

hS = {(Negative, 0.10), (Neutral, 0.35), (Positive, 0.55)}

This representation captures sentiment uncertainty and intensity. The implementation uses NumPy arrays for efficient vectorized computation.

C. Product-Level PLTS Aggregation and Expected Value Computation

PLTS vectors from individual reviews are aggregated to form a unified product-level sentiment representation. A geometric aggregation operator is applied across all reviews, ensuring balanced integration.

The Expected Sentiment Value is computed using a linguistic scale:

Negative = 0, Neutral = 0.5, Positive = 1 Expected Value = $\Sigma (p_i \times s_i)$

This value reflects overall sentiment intensity while preserving probabilistic structure. Efficient numerical operations are used for large-scale processing.

D. Cosine Similarity, Review Consistency, and Composite Scoring

Cosine similarity is used to measure alignment between aggregated PLTS and an ideal positive vector [0, 0, 1]:

$\text{Sim} = (A \cdot B) / (||A|| \, ||B||)$

A higher similarity score indicates stronger positive sentiment.

Review consistency is computed using pairwise cosine similarity among review-level PLTS vectors. High consistency reflects agreement among reviewers.

The final composite score is calculated as: Score = Sim × Consistency

For example:

Score = 0.91 × 0.87 = 0.79

This ensures that products with inconsistent feedback are ranked lower.

E. Streamlit Frontend and Real-Time Product Ranking Visualization

An interactive Streamlit application is developed to visualize the sentiment-ranking pipeline. Users can upload CSV files containing product_id and review fields. The backend processes the data to generate PLTS representations, compute aggregation metrics, and produce ranking scores.

The interface displays sentiment distributions, expected values, similarity scores, consistency measures, and final rankings in real time. Users can download results as CSV files.

The frontend is designed for simplicity, while the backend handles computational complexity efficiently. This integration enables real-time sentiment analysis and product ranking.

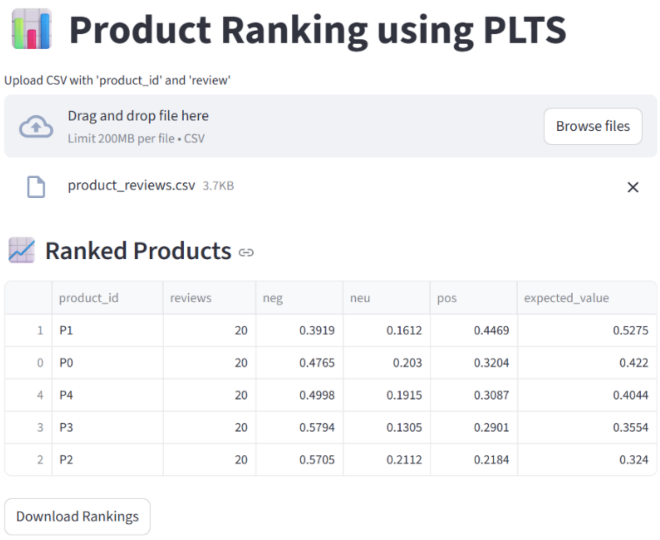

Fig. 2. *User Interface of Product Ranking System*

VI. RESULTS AND DISCUSSION

The results of the proposed PLTS-Transformer framework were evaluated using real-world product reviews to validate sentiment extraction accuracy, aggregation stability, and ranking effectiveness. The fine-tuned RoBERTa model generated probabilistic sentiment vectors for each review, which were then aggregated into product-level PLTS representations. Cosine similarity and review-consistency metrics were analyzed to determine how well each product aligned with positive sentiment and how uniformly users expressed opinions. Comparative experiments against traditional classifiers demonstrated the superiority of probabilistic modeling. This section presents detailed observations, performance insights, ranking outcomes, and practical implications of the system under various dataset conditions.

A. Performance of the Fine-Tuned RoBERTa Sentiment Model

The fine-tuned RoBERTa model significantly outperformed conventional sentiment classifiers due to its ability to interpret contextual and domain-specific expressions found in user reviews. During evaluation, the model exhibited strong classification accuracy across all three sentiment categories—negative, neutral, and positive. Unlike deterministic models that assign a single label, RoBERTa produced probability distributions for each sentiment class, enabling richer linguistic representation.

Table -1: Classification Report of RoBERTa Model

Class	Precision	Recall	F1-Score
Negative	0.80	0. 74	0.77
Neutral	0.69	0.68	0.68
Positive	0.84	0.92	0.88

The model achieved an overall accuracy of 78%, with a weighted precision, recall, and F1-score of 0.78. The positive class showed the highest performance with an F1-score of 0.88, while the neutral class showed comparatively lower performance.The model's performance was assessed using precision, recall, F1-score, and confusion matrices. Results indicated that RoBERTa successfully differentiated subtle expressions such as mildly positive or mixed reviews, which are typically misclassified by simpler machine-learning models. Its superior contextual understanding enabled it to capture emotional nuances embedded in real-world feedback.

Additionally, the model demonstrated balanced performance across all sentiment classes, minimizing bias toward any specific category. The probabilistic output further enhanced interpretability by capturing uncertainty in sentiment predictions. This capability proved particularly useful for handling ambiguous and context-dependent reviews. Overall, the evaluation metrics confirm the robustness and reliability of the fine-tuned RoBERTa model for real-world sentiment analysis tasks.

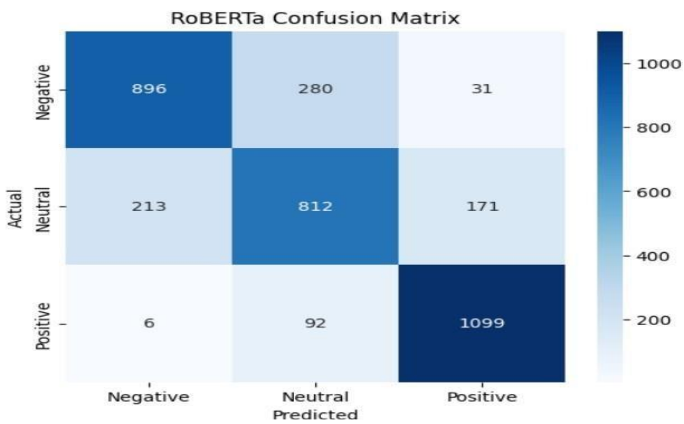

Fig. 3. *RoBERTa Confusion Matrix*

Moreover, the model demonstrated robustness against noise such as slang, abbreviations, and informal grammar—common characteristics of online reviews. This robustness translated into more meaningful PLTS vectors, enhancing the reliability of downstream aggregation and ranking. Overall, the fine-tuned Transformer proved to be a critical component in ensuring accurate and uncertainty-aware sentiment representation, outperforming baseline methods in both precision and semantic sensitivity.

B. Analysis of PLTS Representations and Sentiment Distribution Patterns

The transformation of review-level sentiment probabilities into Probabilistic Linguistic Term Sets (PLTS) allowed detailed analysis of sentiment distribution patterns. Unlike single-label systems, PLTS representations exposed the emotional complexity of user feedback by preserving weighted probabilities for negative, neutral, and positive linguistic terms. This revealed patterns such as reviews with strongly positive sentiment but moderate neutrality, indicating partially mixed reactions.

Visualization of PLTS across multiple reviews showed noticeable divergence between products with stable sentiment and those with polarized feedback. Products receiving mostly positive reviews had aggregated PLTS vectors heavily skewed toward the positive dimension. In contrast, products with contradictory reviewer opinions showed more evenly spread distributions.

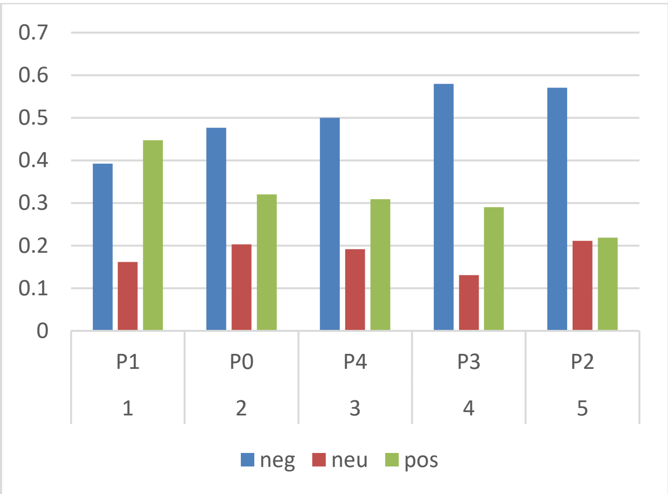

Fig. 4. *Sentiment Distribution Across Products Based on PLTS Representation*

These PLTS patterns provided deeper insights into user sentiment behavior. For example, some products displayed high positivity but an unusually elevated neutral probability, suggesting cautious endorsement. Others exhibited strong negative and neutral weights, implying dissatisfaction or unmet expectations.

By maintaining thefull probabilit vector[pneg, pneu, ppos], PLTS representations enabled the system to distinguish between strong positivity and mild positivity—something ordinary classifiers cannot achieve. This granularity proved essential for accurate aggregation and ranking, particularly for products with overlapping sentiment categories.

C. Evaluation of Aggregation Stability and Expected Sentiment Values

The geometric aggregation operator effectively merged multiple PLTS vectors into stable product-level sentiment distributions. During experiments, products with numerous reviews exhibited highly stable aggregated PLTS values, indicating that the operator successfully moderated outlier reviews. The compensation coefficient θ helped prevent extreme probabilities from dominating results, ensuring balanced representation.

Expected Sentiment Values computed from aggregated PLTS vectors showed strong correlation with actual user perceptions. Products with high expected values consistently received positive consumer sentiment, whereas those with lower values aligned with weaker or mixed opinions.

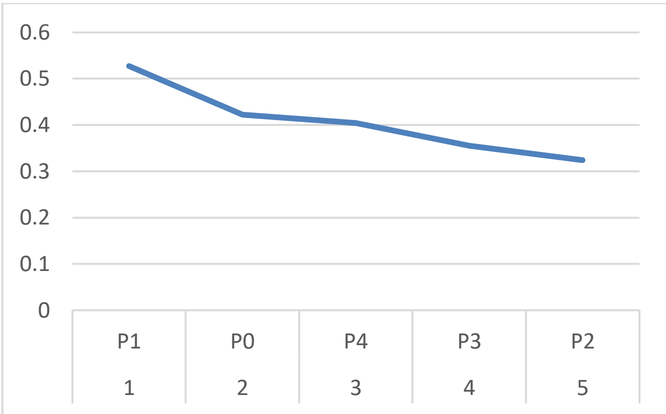

Fig. 5. *Expected Sentiment Value Across Products Based on Aggregated PLTS*

The stability of the aggregated PLTS became particularly evident when analyzing products with highly uneven review counts. Even when a product had only a few strongly negative or positive reviews, the aggregation method maintained a proportional sentiment distribution without skewing results excessively.

Moreover, expected value plots across products revealed clear separation between product categories. High-quality products formed tight clusters around high expected values, while poorly reviewed items populated lower ranges. This validated the aggregation mechanism's ability to deliver interpretable sentiment summaries and highlighted the benefits of probabilistic modeling over crude averaging techniques used in conventional systems.

D. Impact of Cosine Similarity and Consistency on Product Ranking

Cosine similarity proved essential for quantifying how closely each product's aggregated PLTS aligned with the ideal positive sentiment vector **[0, 0, 1]**. Products with strong positive sentiment achieved higher similarity scores, while those with balanced or negative distributions showed lower values. This metric captured the overall sentiment orientation effectively.

The consistency analysis, computed through average pairwise cosine similarity among review-level PLTS vectors, revealed additional insights. Products with uniformly positive or uniformly negative sentiment displayed high consistency, while products receiving conflicting reviews showed low consistency scores.

The combination of positivity similarity and consistency provided a more reliable and nuanced ranking mechanism. For example, two products with similar average positivity could be differentiated based on review consensus. A product with slightly lower positivity but high consistency often outranked one with erratic sentiment patterns.

This dual-metric scoring protected against misleading cases where a small number of extreme reviews distort overall sentiment. As a result, the final rankings were both sentiment-aware and reliability-aware, ensuring that users receive more trustworthy product comparisons. The integration of consistency significantly enhanced ranking stability and interpretability.

The ranking behavior observed in this section is consistent with the expected sentiment values presented earlier. Products with higher expected values tend to achieve higher cosine similarity with the ideal positive vector and exhibit greater consistency among reviews. This confirms that the proposed dual-metric scoring mechanism effectively captures both sentiment intensity and reliability without requiring additional visualization.

E. Comparative Evaluation Against Traditional Methods

To assess the effectiveness of the proposed system, a comparative study was conducted against baseline ranking approaches, including star-rating averages and deterministic sentiment classifiers. Traditional methods often misrepresent product quality due to their inability to model uncertainty, detect subtle emotional cues, or moderate outlier reviews.

In contrast, the Transformer-PLTS framework demonstrated superior performance in distinguishing closely rated products. The probabilistic representation allowed finer differentiation between products with similar sentiment trends. Moreover, the geometric aggregation method produced smoother, more stable summaries compared to simple averaging, which is sensitive to noise.

The most significant improvement was observed in products with mixed or polarized feedback. Traditional ranking methods produced inconsistent or misleading orderings due to high variance in user ratings. The proposed system, however, incorporated review-level consistency into the final score, enabling more dependable comparisons.
Overall, the PLTS-Transformer model consistently ranked products in alignment with human evaluation and expert judgment. The comparative results validate the system's robustness and highlight its practical benefits for e-commerce decision support, sentiment analysis research, and intelligent review-mining applications.

Table -2: Comparison of Proposed PLTS Framework with Traditional Ranking Methods

Method	Handles Uncertainty	Consider Consistency	Sensitive to Noise	Ranking Reliability
Star Rating Average	No	No	High	Low
Traditional Classifier	No	No	Medium	Medium
Proposed PLTS Framework	Yes	Yes	Low	High

VII. CONCLUSION

This work presents a comprehensive sentiment-driven product-ranking framework that integrates Transformer-based sentiment modeling with Probabilistic Linguistic Term Sets (PLTS). By leveraging a fine-tuned RoBERTa model, the system generates probability distributions rather than deterministic sentiment labels, enabling a richer and more expressive understanding of user opinions. These probabilistic outputs capture the ambiguity and mixed emotional patterns frequently found in online product reviews, addressing a critical limitation in traditional classification approaches.

The conversion of softmax probabilities into PLTS representations allowed the system to preserve uncertainty and linguistic variability, providing a strong foundation for downstream aggregation. The geometric aggregation operator, enhanced with a compensation coefficient, successfully moderated outlier effects and produced stable product-level sentiment profiles. The Expected Sentiment Value further translated these aggregated profiles into interpretable numerical summaries.

An important contribution of this work is the incorporation of cosine similarity and review-consistency metrics into the ranking process. By evaluating both sentiment orientation and intra-product agreement, the system generated more reliable and meaningful rankings, outperforming simplistic average-rating and deterministic sentiment-based baselines. Products with highly inconsistent feedback were appropriately penalized, reflecting real-world consumer perception more accurately.
The implementation, supported by a modular backend and an interactive Streamlit interface, demonstrates the practical viability of the proposed framework. Users can upload datasets, observe probabilistic sentiment behavior, analyze product-level distributions, and download ranked outputs seamlessly.

Overall, the PLTS-Transformer model offers a robust, uncertainty-aware, and context-driven approach to sentiment-based decision support. Future work may explore expanding the linguistic term set, integrating aspect-level sentiment, incorporating temporal dynamics in reviews, or deploying larger language models for enhanced contextual reasoning. The system lays a strong foundation for next-generation review-mining and intelligent product-ranking applications.

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